Classification of EMG Signals for Assessment of Neuromuscular Disorders

Anjana Goen

Department of Electronics & Communication, Rustamji Institute of Technology, BSF, Tekanpur, 475005, India
Email: anjana@rjit.org

Abstract—An accurate and computationally efficient means of feature extraction of electromyographic (EMG) signal patterns has been the subject of considerable research effort in recent years. Quantitative analysis of EMG signals provides an important source of information for the classification of neuromuscular disorders. The objective of this study is to discriminate between normal (NOR), myopathic (MYO) and neuropathic (NEURO) subjects. The experiment consisted of 22 pathogenic (11 MYO and 11 NEURO) and 12 healthy persons. The signals were recorded at 30% Maximum Voluntary Contraction (MVC) for 5 seconds. Features of MUAPs extracted in time have been quantitatively analysed. We have used binary SVM for classification. Separation of normal subjects from neuromuscular disease subjects has an accuracy of 83.45%, whereas separation of subjects from the two types of subjects (myopathic and neuropathic) has an accuracy of 68.29% which is again high.

Index Terms—electromyography, myopathic, neuropathic, RBFNN, SVM, SVM ensemble

I INTRODUCTION

Electromyography (EMG) is the study of the electrical activity of the muscle and is a valuable tool in the assessment of neuromuscular disorders. EMG findings are used to detect and describe different disease processes affecting the Motor Unit (MU), which is the smallest functional unit of the muscle. There are numerous neuromuscular disorders that influence the spinal cord, nerves or muscles. Early finding and diagnosis of these diseases by clinical examination and laboratory tests is crucial for their management as well as their anticipation through prenatal diagnosis and genetic counseling. This information is also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases [1].

The purpose of clinical electromyography (EMG) is to analyze the electrical activity from skeletal muscles during rest and during weak and maximal contraction. EMG signal is composed of motor unit action potentials (MUAPs)which is a compound signal generated by the muscle fibers of the MU, and its amplitude, duration, and shape vary in individual muscles according to a number of factors including the number of muscle fibers of the

MU, the spatial distribution of end-plates and the age of the subject. Furthermore, the individual muscle MUAPs vary, and it is insufficient to evaluate a single or a few MUAPs. Thus, MUAPs can be identified and tracked using pattern recognition techniques. The resulting information can be used to determine the origin of the disease, i.e. neuropathic or myopathic. When a patient maintains a low level of muscle contraction, individual MUAPs can be easily recognized, since only a few MUs are active. As contraction intensity increases, more MUs are recruited; different MUAPs overlap, causing an interference pattern (i.e. superimposed MUAPs) EMG signal decomposition and MUAP classification into groups of similar shapes give significant information for the assessment of neuromuscular pathology. Recent advances in computer technology have made automated EMG analysis feasible. A large number of computer-based quantitative EMG analysis algorithms are commercially available or developed, but none of them are broadly accepted for widespread routine clinical use [1].

Traditionally, neurophysiologists assess MUAPs from their shape using an oscilloscope and listening to their audio characteristics. On this way, an experienced neurophysiologist can detect abnormalities with reasonable accuracy. Subjective MUAP assessment, although satisfactory for the detection of unequivocal abnormalities, may not be sufficient to delineate less obvious deviations or mixed patterns of abnormalities. These ambiguous cases call for quantitative MUAP analysis. Quantitative analysis of MUAPs was developed to take this variability into account. The technique compares the mean duration, amplitude, and shape of several MUAPs from a muscle with age-matched controls to document a reduction or increase in the number of muscle fibers per MU as an indication of myopathic or neuropathic lesion respectively [2]. Some automated decision making systems of neuromuscular disorder diagnosis also emerged. For instance cluster analysis techniques for the automatic diagnosis of pathology based on MUAP records [3], Muscle and Nerve Inference Network (MUNIN) which employed a causal probabilistic network for the interpretation of EMG findings [4] and KANDID-a rule-based EMG expert system [5].In most of these systems, the generation of the input pattern assumes a probabilistic

---

model, with the matching score representing the likelihood that the input pattern was generated from the underlying class [6]. In addition, assumptions are typically made concerning the probability density function of the input data. For classifying MUAPs for differentiation of motor neuron diseases and myopathies from normal, different techniques like back propagation (BP), the radial basis function (RBFNN) and the Self Organizing Feature Map (SOFM) have been used [7]. Analyses of surface EMG signals for clinical diagnosis by various research group have produced not good results and hence generally looked with suspicion or have been neglected. Irrespective of the fact SEMG being unreliable for clinical diagnosis Self Organising Feature Maps (SOFM) and the Kohenen Neural Network (KNN) leave one out method for classification is used and had produced good results [8]. Nonlinear parameters were very effective as an input to Fuzzy K-means and Decision trees classifiers [9]. However, the aforesaid techniques used to train the neural network classifiers are based on the idea of minimizing the train error, which is named empirical risk. As a result, limited amounts of training data and over high training accuracy often lead to over training instead of good classification performance.

An overview and comparison of different EMG methods for myopathic evaluation are presented in[10]. Different EMG methods can be helpful when diagnosing myopathies, whereas the most useful are: Manual analysis of the individual motor unit action potentials (MUAPs) and turns–amplitude analyses. Analysis of the firing rate of motor units, power spectrum analysis, as well as multi-channel surface EMG may also be used in the diagnostics, but are not so common. The frequency spectrum of EMG can also be used, but it was shown the analysis of individual MUAPs is more sensitive for detecting myopathic than analysis of the EMG signal frequency spectrum [11].

A. Main Characteristicsof the Neuromuscular Diseases

Neuromuscular diseases are a group of disorders which involves the motor nuclei of the cranial nerves, the anterior horn cells of the spinal cord, the nerve roots and spinal nerves, the peripheral nerves, the neuromuscular junction, and the muscle itself. These disorders cause muscular weakness and/or wasting. From the large number of neuromuscular disorders we have selected neuropathy and myopathy for our study, as their consistency of clinical appearance is good.

Neuropathies (NEURO) describe damage to the peripheral nervous system which transmits information from the brain and spinal cord to every other part of the body. People may experience temporary numbness, tingling, and pricking sensations, sensitivity to touch or muscle weakness. Others may suffer more extreme symptoms, including burning pain, muscle wasting, paralysis or organ or gland dysfunction. In the advanced stages, large motor units also denervate. Motor unit

potentials with duration values that are longer than normal and with increased amplitude are typical findings in neuropathy.

Myopathies (MYO) are a group of diseases that affect primarily skeletal muscle fibers. The symptoms include muscle dysfunction, cramps, stiffness, and spasm. They are divided into two groups, inheritedor acquired. Most muscular dystrophies are hereditary, causing severe degenerative changes in the muscle fibers. They show aprogressive clinical course from birth or after a variable period of apparently normal infancy. One of the most frequently acquired myopathies is polymyosit is, which is characterized by acute or subacute onset with muscle weakness progressing slowly over a matter of weeks. MUAP's with short duration and reduced amplitude are typical findings in patients suffering from myopathy [12]. Fig. 1 shows the structure of normal and myopathic muscle fibers.
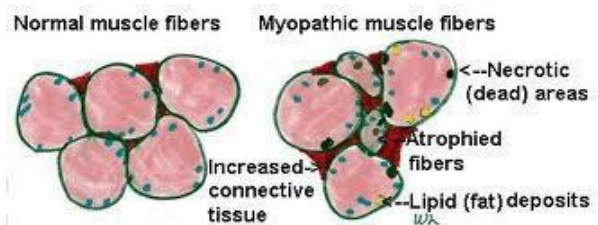

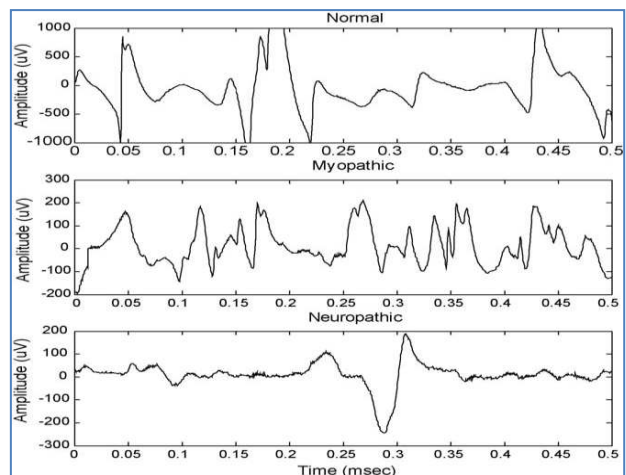Figure 1. Structure of Muscle fibers (Normal versus Myopathic)

Figure 2. Raw EMG signal

Typical EMG waveforms for all the three categories are shown in Fig. 2.

Fig. 3 depicts very well that the frequency of MUAPs are different for NOR, MYO and NEURO group. MYO MUAPs have high frequency and small amplitude whereas the frequency of NOR lies between that of the MYO and NEURO subjects. This paper is organized into5 sections: Section I briefly describes EMG and its characteristics and previous work done by various researchers. Section II describes data preprocessing, MUAP identification, feature extraction and classification of EMG signal. Section III illustrates result section IV discussion and section V ends with conclusion and future prospects.

II MATERIALS AND METHODS

A. Data Acquisitionand Preprocessing

EMG was recorded from the biceps brachii muscle upto30%voluntary contraction for five seconds using the concentric needle electrode with 3-5 mm insertion into the muscle before recording. An UWE HS-30K digital dynamometer was used to verify the contraction level. In low level of muscle contraction individual MUAPs can be easily recognized since only few MUs are recruited. With increasing muscle force the EMG signal shows an increase in the number of activated MUAPs. Before capturing the data prior consent of the subjects was taken and subject's personal data form was filled up. The recording points within the muscle were standardized, with MUAP's recorded from three to five different needle insertions. The electrode was moved at least 3-5 mm between recordings to make sure that different MUAP's were recorded. For a quantitative EMG study, at least 20 MUAP's were recorded. Only 34 subjects participated as it was very difficult to include the subjects with neuromuscular disorders as very few of them gave their consent for recording of the data. Anantialiasing band pass filter (20-1000Hz) was initially applied on the recorded signals, which were then sampled with a sampling frequency of 2KHz at a 12-bitAD converter for good resolution. EMG signal acquisition is depicted in Fig. 3.
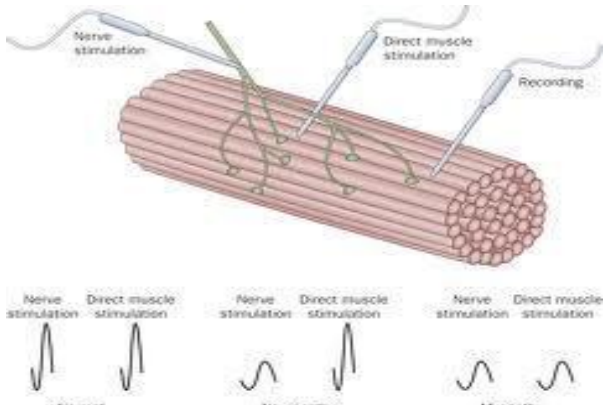

Figure 3. EMG signal acquisition

B. MUAPIdentification

EMG signals are the superposition of the electrical activities of the several motor units. In order to understand the mechanisms pertaining to muscle and nerve control, the EMG signal has to be decomposed into single MUAP and thereafter into Motor Unit Action Potential Trains (MUAPTs). Single threshold method was used to decompose the EMG signals into candidate MUAPs and then further detection and decomposition of the superimposed MUAPs. Using threshold value T, areas of low activity were eliminated and peaks over the calculated threshold T were considered as candidate MUAPs. A window of the length 200 sampling points

were used to identify the peaks and the window was centered at the highest peak if found so, otherwise 200 points were saved as candidate MUAPs. The Threshold T was calculated as follows:

If $\max\{x_i\} > \frac{30}{L}\sum_{i=1}^{L}\mid x_i\mid$,

Then $T = \frac{5}{L}\sum_{i=1}^{L}\mid x_i\mid$,

Else $T = \max\ (\{x_i\}/5)$

The threshold T is made to vary between 30 and 100µV [15].

C. Feature Extraction

Several measurable features of time domain of the EMG signal have been used by various research groups in the computational diagnosis of neuromuscular disorders. These features make us possible to distinguish EMG signal as Normal (NOR), Myopathic (MYO) and Neuropathic (NEURO).

Time domain analysis

Mean and standard deviation of following time domain features have been used[13].

a. Duration (Dur): MUAP beginning and ending was identified by sliding a measuring window of length 3ms and width ± 10 µV.

b. Spike duration (SpDur): Is measured from the first to the last positive spike.

c. Amplitude (Amp): Is the difference between the minimum positive peak and the maximum negative peaks.

d. Area (Ar): Is the sum of the rectified MUAP integrated over the duration measure.

e. Spike Area (SpAr): Is the sum of the rectified MUAP integrated over the spike duration.

f. Phases (Ph): The number of baseline crossings that exceed 25 µV plus one.

g. Turns (T): The number of positive and negative peaks separated from the preceding and following peak by 25 µV.
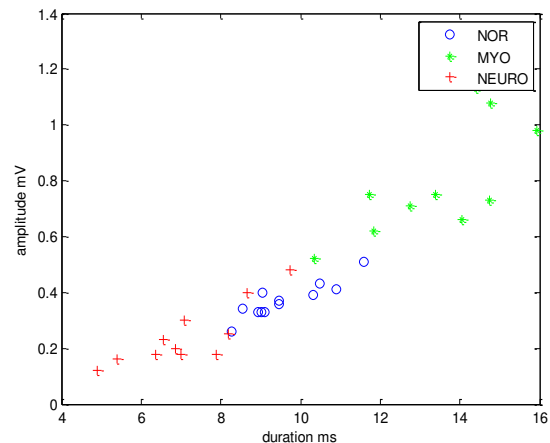

Figure 4.Scatter Plot for Mean Duration and Mean Amplitude for Each Subject

The scatter plot against mean duration and amplitude for each subject, illustrated in Fig. 4 depicts the complexity of the data with no clear boundaries enclosing each group.

TABLE I.   COMPLETE SET OF DATA

DurMn	DurSD	AmpMn	AmpSD	SpDMn	SpDSD	SpAMn	SpASD	PhMn	PhSD	TurMn	TurSD	ArMn	ArSD
8.93	2.77	0.33	0.23	6.05	2.7	0.24	0.17	2.5	0.61	3.1	1.21	0.47	0.38
10.48	2.83	0.43	0.18	4.39	1.74	0.22	0.1	3.15	0.88	3.6	1.05	0.4	0.22
11.6	3.4	0.51	0.3	4.77	2.62	0.25	0.13	2.6	0.5	3	0.56	0.3	0.19
9.11	3.01	0.33	0.19	4.78	2.23	0.2	0.12	2.75	0.97	2.95	0.83	0.29	0.23
9.01	2.04	0.33	0.15	4.86	1.98	0.19	0.07	2.45	0.51	2.75	0.72	0.3	0.21
10.32	2.14	0.39	0.17	5.93	2.87	0.26	0.14	2.95	1	3.35	1.27	0.35	0.19
8.26	2.12	0.26	0.11	5.43	2.61	0.19	0.08	2.4	0.5	3	1.08	0.37	0.27
9.45	1.74	0.37	0.15	5.63	1.85	0.26	0.09	2.3	0.47	2.75	1.07	0.33	0.22
9.45	2.86	0.36	0.21	6.08	2.41	0.25	0.13	2.2	0.41	2.55	0.6	0.39	0.55
10.9	2.37	0.41	0.15	6.82	2.59	0.26	0.09	2.5	0.76	2.75	1.33	0.43	0.29
8.56	3.06	0.34	0.21	4.97	1.63	0.22	0.12	2.55	0.94	3.65	1.27	0.37	0.34
9.05	2.72	0.4	0.18	5.31	2.97	0.27	0.12	2.8	1.01	3.3	1.26	0.51	0.36
15.94	2.37	0.98	0.36	12.98	5.73	0.84	0.4	5.65	2.5	6.2	2.5	0.82	0.34
14.42	3.17	1.13	1.19	7.81	2.65	0.72	0.56	3.75	1.12	5.75	2.79	0.91	0.73
14.78	3.42	1.08	0.49	6.29	2.02	0.62	0.27	3.7	1.63	4.75	2.36	0.72	0.43
14.05	3.69	0.66	0.29	5.48	5.14	0.32	0.27	3.95	1.64	4	1.62	0.41	0.19
12.76	4.65	0.71	0.32	5.86	1.92	0.43	0.19	2.7	0.57	3.05	0.89	0.56	0.3
13.65	4	1.22	0.86	5.82	2.38	0.7	0.51	3.6	1.19	4.05	1.43	0.72	0.5
11.84	3.74	0.62	0.29	4.32	2.84	0.33	0.16	3.05	0.6	3.6	1.05	0.44	0.17
11.73	3.92	0.75	0.57	6.53	3.36	0.48	0.37	4.5	2.84	5.95	3.75	0.67	0.55
14.75	4.52	0.73	0.32	7.63	4.32	0.42	0.22	4.7	1.59	5.55	2.61	0.37	0.13
10.34	2.39	0.52	0.27	5.15	1.97	0.34	0.18	3.3	1.17	3.6	1.05	0.39	0.18
13.39	3.12	0.75	0.39	7.58	3.88	0.53	0.28	4.75	2.15	5.75	2.81	0.74	0.37
8.18	1.52	0.25	0.09	4.36	2.19	0.15	0.08	2.7	1.03	3.1	1.37	0.28	0.19
8.65	3.08	0.4	0.29	3.52	1.32	0.23	0.17	2.75	0.72	2.95	1	0.34	0.24
5.41	1.34	0.16	0.08	2.97	1.31	0.1	0.05	2.5	0.95	3.25	1.37	0.33	0.24
6.87	2.19	0.2	0.14	4.1	1.57	0.13	0.09	2.4	0.75	3.05	1.15	0.24	0.14
4.91	0.98	0.12	0.11	3.45	0.79	0.08	0.07	2.25	0.55	2.4	0.75	0.29	0.24
6.99	2.15	0.18	0.1	4.62	1.48	0.12	0.06	3.05	1.15	3.65	1.57	0.25	0.2
7.89	2.6	0.18	0.1	6.12	2.55	0.15	0.09	2.75	0.97	2.8	0.95	0.21	0.09
6.37	1.76	0.18	0.13	4.57	1.8	0.14	0.12	2.7	0.92	3.05	1.1	0.26	0.2
9.74	2.15	0.48	0.31	4.92	1.77	0.32	0.21	3.25	1.07	3.7	1.38	0.4	0.33
7.07	1.62	0.3	0.12	4.83	1.16	0.22	0.1	2.6	0.94	3.45	1.36	0.44	0.27
6.57	1.22	0.23	0.16	2.9	1.07	0.15	0.15	3.1	1.33	3.1	1.17	0.43	0.4

Note: p values of the data are < 0.05

TABLE II.   MEAN AND STANDARD DEVIATION STATISTICS FOR NOR, MYO AND NEURO SUBJECTS

MUAPs	Duration ms		Amplitude mV		Spike duration ms		Spike area mVms		Phase		Turn		Area mVms	
	Mn	SD	Mn	SD	Mn	SD	Mn	SD	Mn	SD	Mn	SD	Mn	SD
NOR 240	9.60	1.91	0.40	0.16	5.42	2.35	0.23	0.11	2.60	0.71	3.06	1.02	0.38	0.29
MYO 220	13.42	3.54	0.83	0.49	6.86	3.29	0.52	0.31	3.97	1.55	4.75	2.08	0.61	0.35
NEURO 220	7.15	1.87	0.24	0.12	4.21	1.55	0.16	0.11	2.73	0.94	3.14	1.20	0.31	0.23

2.4 MUAP Classification

In this study, we have used electromyography signals from 12 normal and 22 pathogenic (11 MYO and 11 NEURO) subjects at 30% muscle contraction level and examined. A binary SVM classifier, a feed forward network, SVM ensemble and RBFNN has been used as classifier.

Support Vector Machine being linear and binary can be used as a two class classifier. With slight

modifications in the algorithm, it can also be employed for multiclass classification problem [14].

SVM ensemble to improve the limited classification performance of the real SVM, SVM ensemble with bagging or boosting is used. In bagging and boosting the trained individual SVM are aggregated to make a collective decision in several ways such as Majority voting, least squares estimated-based weighting and the double-layer hierarchical combining [15]-[16].

Radial Basis Function Neural Network is a two layer feed forward network in which the hidden layer implements a set of radial basis function e.g. Gaussian functions. The output nodes implement functions as in MLP and the training/learning is very fast and the network training is divided into two stages.

The extracted MUAPs were first classified into normal and pathogenic and the pathogenic MUAPs were further classified into myopathic and neuropathic.

For comparing the results obtained from classifiers, common classifier performance metric shave been used [13]. For a given decision suggested by acertain output neuron, four possible alternatives exist; true positive (TP), false positive (FP), true negative (TN), and false negative (FN). In our study, a TP decision occurs when the positive diagnosis of the system coincides with a positive diagnosis of the physician. A TN decision occurs when the absence of a positive diagnosis of the system agree with that of the physician. The classification rate was computed for both the classifications for all the three classifiers.

$$\text{Classification rate\%} = 100 \times (TP + TN)/ N$$

Also, performance evaluation parameters namely sensitivity, specificity and Positive Predictive Value (PPV) were computed. We have defined Sensitivity is the probability that the test gives a positive result when pathogenic features are tested. Specificity is the probability that a test gives a negative result when normal cases are tested. PPV is the probability that a patient with a positive test is actually pathogenic.

We have used three-fold cross validation using 30 iterations for each of the classifiers. The total MUAPs were divided into the ratio of 35% and 65%. During the first fold, 65% of the data was used as training data for developing the classifier. The remaining part 35% of the data was used as the test data, and the performance evaluation parameters were calculated. This procedure was repeated three times by using a different test set in each fold. The averages of the performance measures obtained in each fold were reported as the final performance measures. In our example out of 34 subjects, test data consisted of 12 subjects and 22 subjects were used for training purposes. More data was utilized for training so that it could be well trained for evaluating the remaining data. Training more data takes more computing time hence small dataset is used but it was compensated with the increase in classification accuracy. The means and standard deviations of the time domain features of each subject were taken as the input feature

vector for all three classifiers namely SVM, SVM ensemble and RBFNN.

III RESULTS

EMG data collected from 34 subjects (12 normal and 22 pathogenic) were analyzed using the methodology described in Section II. Subjects having no history or signs of neuromuscular disorders were considered as normal. The input feature vector for all the three classifiers consisted of mean and standard deviations (Table I and Table II) of each of the time domain parameters of MUAPs. All the algorithms were implemented using MATLAB R2012b.

Table III shows the results of detailed summary of the all the classifiers used in this work. SVM ensemble classifier performed better than the other classifiers. An average of 91.2% classification accuracy was achieved. Table IV depicts average positive predictive value (PPV), sensitivity and specificity for SVM ensemble as 92.2%, 91.1% and 91.9% respectively. The performance of other classifiers is close to the SVM ensemble. RBFNN has PPV (91.5%), sensitivity (90.6%) and specificity (91.4%).

TABLE III. CLASSIFICATION RATE PERCENTAGE

Classification of Subject as	SVM	SVM ensemble	RBFNN
Normal/Pathogenic	87.2	90.1	90.2
Myopathic/Neuropathic	88.4	92.3	91.6

TABLE IV. OVERALL PERFORMANCE EVALUATION RESULTS OF THE THREE CLASSIFIERS

Classifier	PPV(%)	Sensitivity(%)	Specificity(%)
SVM	88.9	87.5	88.8
SVM Ensemble	92.2	91.1	91.9
RBFNN	91.5	90.6	91.4

IV DISCUSSIONS

EMG data collected from 34 subjects were analyzed using mean and SD of time domain features mentioned in Table II. Data diagnostic criteria were based on clinical opinion, biochemical data and muscle biopsy. Only subjects with no history or signs of neuromuscular disorders were considered as normal. Examining the classification rate for each 2-class classification, the highest classification rate was obtained for the pathogenic classification using SVM ensemble as classifier. As shown in Table III and IV, the SVM ensemble improved significantly the classification rate and overall performance as compared to the other two algorithms. The RBFNN result was very close to SVM ensemble.

In this work, pattern recognition techniques forthe classification of MUAP's were investigated using an artificial neural network technique based on supervised learning for SVM, modified SVM and RBFNN. ANN

techniques used yielded a higher classification rate and seem more appropriate for the classification of MUAP's because of their ability to adapt and to create complex classification boundaries. The modified SVM optimizes the classification boundaries through slight adaptation of the weights vectors. Moreover, the ANN technique presented in this study performed well even with a limited amount of data. In conclusion, the pattern recognition techniques as described in this work make possible the development of a fully automated EMG signal analysis system which is accurate, simple, fast and reliable enough to be used in routine clinical environment. Future work will evaluate the algorithms developed in this study on EMG data recorded from more muscles and more subjects. In addition, this system may be integrated into a hybrid diagnostic system for neuromuscular diseases based on ANN where EMG [17], muscle biopsy, biochemical and molecular genetics findings, and clinical data may be combined to provide a diagnosis [18].

Table V shows the summary of the EMG classification. Fast Fourier transform (FFT) and principal component analysis (PCA) was used on sEMG signals taken from bicep brachii muscle and the classifications of neuromuscular disorders was performed using multilayer perceptron (MLP) and Support Vector Machine (SVM) classifier in reference [19]. They obtained the correct classification of 85%. Ref. [20] used sEMG signal, recorded from the biceps brachii muscle, and extracted features using multi scale entropy and wavelet transform. They classified subjects healthy/patient with 80.5% accuracy and three-class classification (healthy/myopathic/ neuropathic) with accuracy of 69.4% using SVM ensemble classifier. Ref. [21] classified EMG signals to normal, myopathic and neuropathic classes using two stage classifier RBFNN and decision tree with an accuracy of 88.7%. Ref. [22] analysed EMG signals using Autoregressive (AR) analysis and the extracted features was applied to neurofuzzy system. The classification performance was evaluated for the three classes normal, myopathy and neuropathy with an accuracy of 90% using neurofuzzy classifier. In the above discussed works, EMG signal was mainly analysed in time and frequency domain. We achieved two-class classification with an accuracy of 91.2% using a simple technique (Table V). This classification accuracy can be further increased using more diverse features and more EMG data in each group. The comparison should take into consideration that different EMG analysis methods may focus on different MVC levels or different muscles. For this reason only qualitative comparisons and conclusions can be drawn.

The proposed approach can provide a valuable tool to neurophysiologists for MUAP classification. MUAPs features are computed and the MUAPs can be classified according to their pathology. The extracted information is valuable for the patient diagnosis irrespective of the fact that the results produced are based only on features extracted from the MUAP. In clinical practice, neurophysiologists make considerable use of patient's clinical data while performing diagnosis. Hence, further research is needed on the effect of such clinical data on the classification outcome.

TABLE V. COMPARISON OF OUR WORK WITH OTHER REPORTED WORKS FOR MUAP CLASSIFICATION

Work	Approach Type	Accuracy (%)
Guler et al.(2005)	Feature-based	85.4(3-class)
Katsis et al.(2007)	Feature-based	88.7(3-class)
Istenic et al.(2010)	Multiscale entropy, WT	80.5(2-class) 69.43(3-class)
Kocer et al.(2010)	AR coefficients	90(3-class)
This work	Feature-based	91.2(3-class)

V CONCLUSIONS

Muscle is a vital organ of the body responsible for movements. Study on EMG is very broad starting from the design of electrodes to recording techniques, analysis methods and application for various purposes. Many studies have been conducted in an attempt to characterize different muscle disorders using traditional methods like time and frequency domain analysis. In this work, an integrated binary classifier based on SVM and modified SVM and RBFNN has been adopted for differentiating the neuromuscular disorders. Experimental results show that the binary SVM ensemble classifier can be effectively trained for MUAPs diagnosis. We have managed to obtain an accuracy of 91.2%, sensitivity of 91.1%, specificity of 91.9% and PPV of 92.2%. The diagnostic results could be further improved in future works with larger data sets and utilizing other features sets may be linear or nonlinear as an input to the SVM.

In the last, we can say that the method combines high performance, interpretability of results, automated mode of operation and small training set. It is therefore highly suitable for a clinical decision support system, providing a valuable tool to neurophysiologists for MUAP classification.

REFERENCES

[1] A. Subasi, M. Yilmaz, and H. R. Ozcalik, "Classification of EMG signals using wavelet neural network," *Journal of Neuroscience Methods,* vol. 156, pp. 360–367, 2006.

[2] M. Nikolic and C. Krarup, "EMG tools, an adaptive and versatile tool for detailed EMG analysis," *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 10, October 2011.

[3] J. L. Coatrieux, P. Toulouse, B. Rouvraisand, and R. L. Bars, "Automatic classification of electromyographic signals," *EEG Clin. Neurophysiol.,* vol. 55, pp. 333-341, 1983.

[4] S. Andreassen, S. K. Andersen, F. V. Jensen, M. Woldbye, A. Rosenfalck, B. Falck, U. Kjaerluffand, and A. R. Sorensen, "MUNIN-An expert system for EMG," *Electroenceph. Clin. Neurophysiol*, vol. 66, 1987.

[5] A. F. Frederiksen and S. M. Jeppesen, "A rule-based EMG expert system for diagnosing neuromuscular disorders," in *Computer Aided Electromyography and Expert Systems*, J. E. Desmedt, ed. New York: Elsevier Science Publishers B.V., 1987, pp. 289-296.

[6] R. P. Lippmann, "An introduction to computing with neural nets," *IEEE ASSP Mag.*, 1987.

[7] C. I. Christodoulou and C. S. Pattichis, "Unsupervised pattern recognition for the classification of EMG signals," *IEEE Transactions on Biomedical Engineering,* vol. 46, no. 2, February 1999.

[8] P. A. Kaplanis, C. S. Pattichis, C. I. Christodoulou, L. J. Hadjileontiadis, V. C. Roberts, and T. Kyriakides, "A surface electromyography classification system," in *IFMBE Proc. Medicon and Health Telematics 2004, X Mediterranean Conference on Medical and Biological Engineering*, vol. 6.

[9] U. R. Acharya, E. Y. K. Ng, G. Swapna, and Y. S. L. Michelle, "Classification of normal, neuropathic, and myopathic electromyograph signals using nonlinear dynamics method," *Journal of Medical Imaging and Health Informatics*, vol. 1, pp. 375–380, 2011.

[10] C. D. Katsis, Y. Goletsis, A. Likas, D. I. Fotiadis, and I. Sarmas, "A novel method for automated EMG decomposition and MUAP classification," *Artificial Intelligence in Medicine,* vol. 37, pp. 55-64, 2006.

[11] A. F. Frederiksen, "The role of different EMG methods in evaluating myopathy," *Clinical Neurophysiology*, vol. 117, no. 6, pp. 1173– 1189, 2006.

[12] W. Trojaborg, "Motor unit disorders and myopathies," in *A Textbook book of clinical Neurophysiology,* M. A. Halliday, R. J. Butler and R. Paul, Eds. New York: Wiley, 1987, pp. 417-438.

[13] C. S. Pattichis, C. N. Schizas, and L. T. Middleton, "Neural network models in EMG diagnosis," *IEEE Transactions on Biomedical Engineering*, vol. 42, no. 5. pp. 486-496, May 1995.

[14] V. P. Vapnik, *The Nature of Statistical Learning Theory*, Springer Verlag, New York, 1995.

[15] H. Kim, S. Pang, H. Je D. Kim, and S. Y. Bang, "Constructing SVM ensemble," *Elseveir*, vol. 36, no. 12, pp. 2757-2767, December 2003.

[16] M. Claesen, F. D. Smet, and B. D. Moor. (March 2013). Ensemble SVM. [Online]. Available: http://esat. kuleuven.be/sista/ensemblesvm/

[17] R. C. Eberchart and R. W. Dobbins, *Neural Network PC Tools: A Practical Guide,* New York: Academic. 1990

[18] C. N. Schizas, C. S. Pattichis, and C. A. Bonsett, "Medical diagnostic systems: A case for neural networks," *Technol.*, *Health Care*, vol. 2, pp. 1–18, 1994.

[19] N. F. Güler and S. Koçer, "Classification of EMG signals using PCA and FFT," *Journal of Medical Systems,* vol. 29, no. 3, pp. 241-250, June 2005.

[20] R. Istenic, P. A. Kaplanis, C. S. Pattichis, and D. Zazula, "Multiscale entropybasedapproach to automated surface EMG classification of neuromuscular disorders," *Med BiolEngComput.* vol. 48, no. 8, pp. 773-781, August 2010.

[21] C. D. Katsis, T. P. Exarchos, C. Papaloukas, Y. Goletsis, D. I. Fotiadis, and I. Sarmas, "A two-stage method for MUAP classification based on EMG decomposition," *Computers in Biology and Medicine,* vol. 37, no. 9, pp. 1232-1240, 2007.

[22] S. Kocer, "Classification of EMG signals using neuro-fuzzy system and diagnosis of neuromuscular diseases," *Journal of Medical Systems,* vol. 34, pp. 321-329, 2010.

Anjana Goen was born in India completed her graduation B.E.(Electronics & Telecommunication) in 1991 from Ranchi University, India and her master degree M.Tech Telecom Technology in 2008 from RGPV, India. Presently she is doing PhD in biomedical signal processing from Jiwaji University, Gwalior, India. She had 20 years of teaching experience. She served as lecturer in BIT Dhanbad and MITS Gwalior. Since 2000, she is an Assistant Professor at RJIT, Tekanpur, Madhya Pradesh, India. She had published more than 5 papers in International Journals & Conferences. She had presented more than 10 papers in International & National Conferences. Her interest lies in Digital Signal and Image processing and especially in biomedical signal and image processing. Ms Goen is life member of IETE. She had also been associated with CSI and ISTE, India.